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What attracts vehicle consumers' buying: a Saaty scale-based VIKOR (SSC-VIKOR) approach from after-sales textual perspective?

Fuli Zhou ¹, Ming K. Lim ^{2,3}, Yandong He ^{4*}, Saurabh Pratap ⁵

¹ School of Economics and Management, Zhengzhou University of Light Industry, Zhengzhou, China

² College of Mechanical Engineering, Chongqing University, Chongqing, China

³ Center for Business in Society, Coventry University, Coventry, United Kingdom

⁴ Research Center on Modern Logistics, Graduate School at Shenzhen, Tsinghua University, Shenzhen, China

⁵ Department of Mechanical Engineering, Indian Institute of Information Technology, Design & Manufacturing Jabalpur, Madhya Pradesh, India

Abstract

Purpose: The increasingly booming e-commerce development has stimulated vehicle consumers to express individual reviews through online forum. The purpose of this paper is to probe into the vehicle consumer consumption behaviour and make recommendations for potential consumers from textual comments viewpoint.

Design/methodology/approach: A big data analytic-based approach is designed to discover vehicle consumer consumption behaviour from online perspective. To reduce subjectivity of expert-based approaches, a parallel Naïve Bayes approach is designed to analyse the sentiment analysis, and the Saaty scale-based (SSC) scoring rule is employed to obtain specific sentimental value of attribute class, contributing to the multi-grade sentiment classification. To achieve the intelligent recommendation for potential vehicle customers, a novel SSC-VIKOR approach is developed to prioritize vehicle brand candidates from a big data analytical viewpoint.

Findings and Originality/value: The big data analytics argue that “cost-effectiveness” characteristic is the most important factor that vehicle consumers care, and the data mining results enable auto-makers to better understand consumer consumption behaviour.

Research/Practical implications: The case study illustrates the effectiveness of the integrated method, contributing to much more precise operations management on marketing strategy, quality improvement and intelligent recommendation.

Originality/value: Researches of consumer consumption behaviour are usually based on survey-based methods, and mostly previous studies about comments analysis focus on binary analysis. The hybrid SSC-VIKOR approach is developed to fill the gap from the big data perspective.

Keywords: Sentiment value; Parallel Naïve Bayes method; Sentiment classification; Saaty scale-based VIKOR (SSC-VIKOR); Intelligent recommendation

Article Type: Research paper

1 Introduction

With rapid development of the automobile industry, China has become the nation with the most annual vehicle production amount from all over the world since 2009 (Zhou, Lim et al. 2019). To improve vehicle product performance and narrow the gap with developed automobile organizations, the quality improvement management practice has been performed by Chinese domestic auto industries in the light of the warranty data and global quality research system (Kim et al. 2007; Zhou, Lin, Wang et al. 2016). However, with increasing vehicle consumers and soaring open environment, the explosively growing quality feedback and massive data produced by vehicle users are flowing into the industrial organizations.

The mass textual comments of vehicle consumers play an increasing significant role on the product marketing and brand reputation, also providing valuable guidance on the development of the industrial organizations (Tiwari et al. 2018). Compared with traditional continuous improvement on the basis of maintenance and warranty data, there are increasing automobile industries focusing on the voice of consumers like textual comments, customer complaints and spreading rumors (Zhou, Wang and Samvedi 2018). This situation leads to the innovative quality improvement practices performed and employed by auto-factories concerning qualitative information of vehicle users (Donauer et al. 2015; Shah et al. 2016). It is the consumers' feedback drives the continuous improvement and un-conformity re-correction (Shah et al. 2016; Zhou, Wang et al. 2019; Zhou, Wang and Samvedi 2018). Those organizations which can take full advantage of the mass data to provide guidance on production and marketing operations will be regarded as a triumph (Guajardo et al. 2016).

Furthermore, the booming development of internet and e-commerce has motivated the online interactive communication, and product consumers show an increasing tendency to share the consumption experience and product use cognition through the internet (Su et al. 2019; Wamba et al. 2018). With rapid development of information technology and electronic commerce, users and consumers prefer to express their requirements, product using experiences and individual evaluation using a more understandable comments, such as texts, pictures and expressions, rather than the traditional parameters and structured information (He et al. 2019; Wang et al. 2016; Pappas 2016). The individual-level data and interactively textual comments have been accumulated in an increasingly extraordinary speed (Tiwari et al. 2018). The soaring availability of consumer-oriented mass data provides both automobile organizations and vehicle users with unprecedented chances to tailor decisions to the requirements and behavior preferences of vehicle consumers (Wei and Zhang 2018). In addition, potential users tend to focus on the consumers' experience information who has bought the product, instead of specific product parameters provided by the manufacturer. Therefore, it is of great significance to identify the useful evidence from mass consumers' consumption information (Ziegele et al. 2017).

The data mining management practice on fast selling goods based on textual comments of consumers have been performed and analyzed from online mass data, which contributes to more precise operations management on consumers' requirement identification, marketing policies establishment, strategic improvements and brand promotion (Hardesty and Bearden 2009; Quoquab et al. 2017). With an increasing popularity of online shopping and commentary exchanges, the consumer behavior mining from the textual comments are

studied for consumable products, especially those daily consumption goods in Alibaba and Jingdong online mall (Mengdi Li et al. 2018; Quoquab et al. 2017). However, there is little similar practice on industrial assembly products, like machine, ship and vehicles etc.

The sentiment analysis, regarding as a data mining technique, was usually used to scrutinize the consumers' attitude on experienced products (Wu et al. 2017; Zhang et al. 2011; Zhang et al. 2018). Also it can assist organizations to identify the customer preferences and purchasing willingness (Hung and Chen 2016, Yang et al. 2018). Recently, a vast majority of publications on sentiment analysis have been studied by researchers and practitioners from the big data perspective through machine learning and deep learning approaches (Jha et al. 2018; Qiu et al. 2018; Tripathy et al. 2017). Sentiment classification is performed to analyze the consumers' behavior in terms of review item, word text, sentence and document-level. Different text representation approaches including TF-IDF, LSI and multi-word method are studied and discussed, as well as the big data analytics-based mining techniques for different industrial application (Yuan et al. 2018; Zainuddin et al. 2018; Zhang et al. 2011). The word database used in previous textual comment analysis is mostly fixed and not up-to-date, ignoring the terminology, expression picture and expression etc. non-structural data in the website. Also, the previous sentiment analysis fails to take the discrepancy of object attribute into account, and few associate with emotional word database on the sentimental description of a comment object. Besides, most of researches on sentiment analysis tend to focus the polarity classification, that is, positive and negative one, instead of the multi-grade classification in the light of emotional intensity or sentimental value.

To fill the gap, the modified AHP model integrating Saaty scale-based grading method and Naïve Bayes classifier is designed to derive the consumers' preference from textual comments. To the best of our knowledge, this work is the first to examine the vehicle consumers' consumption behavior based on the multi-grade sentiment classification from the textual comments, also providing an objective recommendation for potential users. The contributions of this research are twofold: ① this study extends the automobile product management practice by developing a big data analytic-based approach to identify the consumers' preferences from the textual comment viewpoint; ② the integrated SSC-VIKOR method developed enables to make recommendations for potential vehicle buyers by making use of the utilization information from end-users.

The reminder of this paper is organized as follows. A literature review is presented and discussed in the following section. Subsequently, the integrated research of data mining with consumer's behavior analysis using big data analytics is designed, followed by the proposed SSC-VIKOR method and implementation details. The results of consumers' preferences are mined and discussed in Section 4. Section 5 presents theoretical implications and managerial insights. Finally, we end this research with conclusions.

2 Literature review

2.1 Consumers' behavior

The e-commerce consumption and online world wide web have been focused and studied to probe into insights of consumer buying behavior (Rahman et al. 2018). The in-depth understanding on consumer behavior facilitates to the more precise managerial decision-making (Vieira 2008; Wei and Zhang 2018). A self-constructed questionnaire is designed, and results of the empirical study on Dhaka City found the security of payment

system and the satisfactions are the most significant factors that online consumers concerned (Rahman et al. 2018). The consumer behavior is a dynamic process with the motivation and stimulus of organizational strategy, and the insightful analysis on consumers requirement and preferences contribute to the development of strategic thinking (Meijkamp 2001).

The consumers' behavior plays a significant role on strategic operations management of industrial organizations. To identify the influence of consumer consumption behavior on the marketing strategy, the survey-based study using statistics analysis is employed to probe insight to the nature of book-store's activities (Remondes 2018). Castillo-Manzano et al. (2018) compared the discrepancy of consumer behavior between hub airports and regional malls, as well as influence of airport mall on passengers' consumer behavior. To develop more suitable marketing strategies, the consumer behavior of electricity market had been investigated by a survey-based study (Rowlands et al. 2010). Nicholson and Xiao (2011) developed behavioral perspective model (BPM) explanatory framework to discover the crucial elements influencing the social marketing strategy.

Many kinds of product consumption behaviors are studied by traditional statistics analysis methods in previous publications, especially for fast products. To analyze the dynamic changes of consumers' purchasing determination, a hierarchy scoring method is developed to compute the position of content items, and the mass online data analysis improves the estimation and predictions of consumers' behavior (Scholz et al. 2018). Tan et al. (2018) proposed a questionnaire approach using face-to-face investigation to scrutinize the returning and recycling preferences of residential customers' behavior, facilitating to the obsolete mobile phone management. The correlation analysis between Google Trends-based search volumes and household consumption behavior is conducted, and the Pearson coefficient index is analyzed to assist better understand the household demand for fish sauce in Japan (Nakano et al. 2018). The budget behavior is mined to assist financial professionals to better understand the consumer budgeting behavior in the light of mental accounting and behavioral hierarchy (Xiao and O'Neill 2018). Visser et al. (2018) studied the discrepancy of different attribute items for consumers of household appliances, and empirical results argued that much more customers tend to buy a reliable, durable product instead of a sustainable and energy-saving one. Due to the existing discrepancy of nations, area and gender, consumer consumption behaviors on making expensive purchase decision or risky determination have proven to be significantly different. The specific differences on cancer treatment medicine in terms of trust belief levels are investigated using a large cross-cultural sample, which facilitates to consumers segmentation and precise marketing based on its corresponding characteristics (Strang 2018). Liu et al. (2018) developed a dynamic model to study the different consumer purchase behavior on buying base product and add-on product concerning compatibility constraints. The empirical analysis argued that the inventory of add-ons showing an obvious impact on the consumer purchase behavior of base products.

2.2 Sentiment classification

Sentiment classification, as a branch of natural language processing (NNP) study, is the process of expolring emotions, ideas, and intrinsic thoughts in the commented review items (Rana et al. 2018). The suvey-based or questionnaire-oriented research design has proven to be effective to scrutinize the consumer behavior, where the pre-design on scale and item in a structured way is the prerequisite of the empirical study (Dailey and Ulku

2018; Heesen and Madlener 2018; Kraft et al. 2018). With accumulated un-structured review and textual comments flowing into the industrial auto-factories, the sentimental analysis of vehicle product consumers assists to examine peoples' attitudes, sentiments, evaluations and emotions in the favor of product and organizational brand.

However, the consumers' consumption behavior analysis with a large scale national sample is limited (Calheiros et al. 2017). To deal with the large amount un-structured information, the big data analytic techniques are developed to improve the efficiency. Arulmurugan et al. (2017) proposed an emotional modeling approach for sentiment analysis concerning the human feeling, and the integration of SVM, Naïve Bayes and Neural network techniques with joint segmentation method is developed to improve the performance of the sentence level sentiment classification. Considering the discrepancy of sentiment expression for different types of sentences, Chen et al. (2017) proposed a divide-and-conquer method to deal with the various sentence-type sentiment classification. Catal and Nangir (2017) developed a vote algorithm by combining SVM, Naïve Bayes, and Bagging approach to deal with Turkish sentiment classification. Besides, the machine learning-based approach (SVM and Neural Network technique) can deal with the document-level sentiment analysis, assisting organizations to discover meaningful information of consumers (Tripathy et al. 2017). To reflect multiple sentimental states of product consumers, Liu and Chen (2015) developed a multi-label sentiment analysis method for microblogs review classification. To consider the polarity of commented word itself, the word-level information from lexicon and tweet-level sentiment label from distant supervised information are both taken into account in learning approach, demonstrating much better performance on benchmark cases (Xiong et al. 2018).

Lexicon-based and machine learning based methods are two typical approaches for sentiment classification (Liu and Chen 2015, Yusof et al. 2015). To improve the efficiency in industrial scenarios, the sentiment knowledge and lexicon-based word study are embedded into the sentimental classifier. The textual comments usually contain the subjective expression and objective content, and the word segment and extraction is the primary for sentiment analysis. To deal with the ambiguity of humans' language, the word sense disambiguation WSD-based SentiWordNet lexicons are constructed to sentiment analysis (Hung and Chen 2016). To identify the sentimental emotion of subjective comments, the sentiment category is performed by applying machine learning techniques, and most studies are polarity classification (positive, negative or neutral attitude). In order to resolve the noisy in massive Twiter message, the heterogeneous sentiment knowledge including contextual similarity knowledge, word-sentiment knowledge and contextual polarity knowledge are employed and taken into account to the traditional sentiment classifier (Wu et al. 2016). To consider the subtle interactions among commented words, reviewed consumers and products, the heterogeneous network liking products, consumers and commented words was embedded into neural network to perform sentiment classification (Gui et al. 2017). Due to the discrepancy of sentiment expression in different domains, Bollegala et al. (2013) proposed a sensitive distributional thesaurus through labeled data to overcome the cross-domain sentiment classification. To tackle the shortage of labeled data in targeted domain, the

multi-source-based domain-specific sentiment classifier is developed, and an ADMM optimization algorithm is designed to solve the programming formula (Wu et al. 2017).

In practical, there are multi-state emotions of product consumers, and a few researches can reflect multi-grade sentiment. However, most publications on sentiment analysis focused on polarity classification (Asgarian et al. 2018, Rana et al. 2018).

2.3 Vehicle product recommendation

The product recommendation has been regarded as a multi-criteria decision-making problem with respect to multiple indexes (Chen et al. 2010; Wang 2015; Xinke Li et al. 2018). To make purchasing determination, the key performance indexes or criteria were formulated at first, followed by the compromising solution generation. Many expert judgement-based methods have been employed to prioritize the product candidate in a subjective way, like Delphi technique, AHP, ANP and MCDM-based approaches (Büyüközkan et al. 2018; Zhou, Wang and Samvedi 2018). Even the fuzzy-based techniques are employed to deal with the uncertainty and ambiguity of the decision making process, the objectivity is limited due to the lack of enough evaluation data. To overcome the ambiguity that short queries cannot express the actual idea, Song et al. (2014) developed a novel query recommendation technology using a hybrid semantic similarity measurement approach.

As the fuzzy-based techniques are usually embedded with expert-oriented judgements and language variables, this kind of applications are limited due to subjectivity or bias. In order to reduce the subjectivity of expert-based analysis methods, big data analytics-based approaches are increasingly employed to investigate the consumers' preferences and purchasing willingness, as well as the product recommendation using the ranking prioritization. Duong et al. (2017) developed a novel collaborative filtering approach based on fuzzy neural network to perform the video recommendation concerning the users' behaviors. Chang et al. (2013) proposed an intelligent recommendation system for digital TV programme using cloud computing technique. To make the personalized recommendation for forum users, a novel learning-to-rank decision-making framework combining content-based and collaborative features was introduced and applied in real industrial applications (Bach et al. 2016).

However, with the integration of soaring data and information in real-world, how to deal with the massive comments with high efficiency has become another obstacle. Ali et al. (2018) presented a knowledge-based reasoning and recommendation framework using a semi-automatic mapping approach to turn the intellectual activity recommendation into practice. The parallel content-based recommendation system was constructed using Hadoop Map Reduce framework to improve the efficiency facing with the large scale of massive data (Gautam and Bedi 2017). Therefore, we also need to focus the efficiency of big data analytics algorithm.

3 Research design and methodology

In order to probe insight to the consumer consumption behavior from textual comment perspective, the non-structured word and attribute class need to be processed in advance for sentiment analysis and behavior mining. This section presents the integrated SSC-VIKOR approach, as well as the developed implementation stages.

3.1 Attribute feature extraction

According to characteristics of textual comment, the following textual structure needs to be focused (Mengdi Li et al. 2018): ① sentiment word or emojis picture; ② positive adverb+emotion word or emoji picture; ③ negative adverb+ emotion word or emojis picture; ④ degree word of emotion + positive adverb+emotion word or emojis picture; ⑤ degree word of emotion+ negative adverb+ emotion word or emojis picture. The attributes reflect characteristics and specific evaluations of product, which can be divided into essential attributes and non-essential attributes. The vehicle performance is described and reflected by series of attribute sets, including brand name, type, color, and price etc. The essential attributes are those that can distinguish the object from other different counterparts. While, other attributes like price, power and maneuverability can not be regarded as the essential characteristics. The classified hierarchy multi-level attribute set is illustrated in Fig. 1.

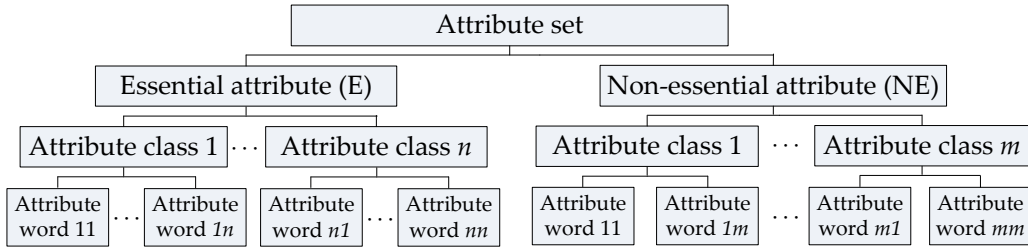


Figure. 1 The hierarchy multi-level attribute set of textual comment

(1) Attribute sets

The attribute words can be extracted from the attribute class, and the PMI algorithm is employed to derive the attribute feature words (Du et al. 2016). Combining the text synonymous analysis with human-aided judgement on the extraction of attribute words, the following PMI calculation in Eq. (1) is used to derive feature words.

$$PMI(AC, AT) = \log \left\{ \frac{P(AC, AT)}{P(AC) \cdot P(AT)} \right\} \quad (1)$$

Where, AC is the attribute class, AT is the attribute word. P denotes the occurrence probability, and the same attribute word is recorded only once when it occurs one or more times in the same comment.

(2) Relative importance of attribute word based on TF-IDF algorithm

The relative importance of attribute word is affected by occurrence frequency and number of comment items. To obtain the relative importance of the different attribute word, the Term Frequency-Inverse Document Frequency (TF-IDF), one kind of statistics technique, is employed to calculate the attribute factor α in Eq. (2) (Ali and Mohamed 2017; Yahav et al. 2019).

$$\begin{aligned} TF &= \text{Occurrence frequency of word in comments} / \text{total comment items} \\ IDF &= \log[\text{total comment items} / (\text{comment including attribute words} + 1)] \\ \alpha(TF-IDF) &= TF * IDF \end{aligned} \quad (2)$$

The TF-IDF algorithm reflects that the attribute word weight is closely related to its occurrence frequency and the number of comment items (Chang et al. 2013; Zhang et al. 2011).

(3) Establishment of sentimental dictionary database

The perfect sentiment dictionary is indispensable to conduct attribute feature extraction (Hung and Chen 2016; Jha et al. 2018). The <Cnki word set for sentiment analysis database (Chinese)>, associating with the adverb set, is employed, and specific steps are as follows.

Step 1 : Sentimental word database construction.

Step 2 : Construction of adverb set.

Step 3 : The extraction of adverb and emotional word. Based on the two-word pattern illustrated in Table 1, the sentimental comments with attribute words are extracted, where the sentimental comments cater to one of the stated patterns "<attribute, sentiment> form".

Table 1 Emotional pattern with two-words

Patterns	1st text	2nd text	3rd text
Pattern 1	adjective	noun	arbitrary word
Pattern 2	adjective, adverb	adjective	non noun
Pattern 3	noun	adjective	non noun
Pattern 4	adjective	adjective	non noun
Pattern 5	adjective, adverb	verb	arbitrary word

3.2 Naïve Bayes classifier

3.2.1 Naïve Bayes method

Naive Bayes method, as one of the prevailing machine learning techniques, is widely used in the classification study (Bermejo et al. 2014; Lee 2015; Taheri et al. 2014). The implementation steps are illustrated by the following equations.

Step 1 : Prior probability calculation ;

$$P(c_i) = \text{Number of comment on } c_i / \text{Total exercised comment items} \quad (3)$$

Where c_i represents the attribute class.

Step 2 : Calculation of the feature item $P(f_j|c_i)$, that the probability of feature f_j belongs to attribute class c_i .

$$P(f_j|c_i) = \text{Occurrence of } f_j \text{ in comment } c_i / \text{Occurrence of all words in } c_i \text{ class} \quad (4)$$

Step 3: Analysis of unclassified comment based on posterior probability that w belongs to class c_i . The classification with the highest posterior probability could be regarded as the unclassified category. And the maximum posterior probability c_{wb} is calculated as Eq. (5) shows.

$$c_{wb} = \arg \max_{c_i \in C} \left\{ P(c_i) \prod_{i=1}^n P(f_j|c_i) \right\} \quad (5)$$

3.2.2 Parallel Naïve Bayes classifier

Due to the great amount of the textual comment processed, the efficiency of traditional Naïve Bayes classifier is influenced by the storage way of training samples. To improve the efficiency of the classification, the parallel Map/Reduce framework is employed to reduce transmission time by distributing the dataset in every node. The parallel Naïve Bayes classifier is proposed to analyze the sentimental attitude of textual comments.

(1) Data preprocessing

The pre-processing of the collected data is completed by a Hadoop Job, including participle of the textual comments and extraction of feature attributes. The following pair-wise information is generated in the form of <ID, fea1 fea2.....feaN>, whose psuedo code is as follows.

Input: Training samples

Output: <ID, fea1 fea2, ..., feaN>

Map:

NLPIR (file):

#Participle

Emotion dictionary read

Put every word in dictionary into hashset

Feature attributes extraction

If hashset contains word

Keep it as a feature

Context.write (ID, fea1 fea2.....feaN)

Combiner/Reducer:

Context.write (ID, fea1 fea2.....feaN)

(2) Training of the established classifier

The training samples are conducted by two Hadoop Jobs, including the calculation on the prior probability and the conditional probability of feature attribute. The pseudo code of prior possibility calculation is shown below:

Input: comment_resule.txt

Output: <ID, Num>

Map:

Context.write (ID, 1)

Combiner/Reducer:

Num=0;

Perform statistics analysis on classified comment item

#Addition operation

For each value:

Num=Num+v;

Context.write (ID, Num);

After the prior possibility calculation, the comment items in different categories are stored in "CommentCount.txt" file, and the pseudo code for conditional probability deduction is illustrated as follows.

Input: comment_resule.txt

Output: <fp, count>

Map:

Conduct statistics analysis on the basis of attribute lexicon

For each word p in file

Context.write ($fp, 1$):

Combiner/Reducer:

Count=0;

#Addition operation

For each value v

Count=count+ v

Context.write (fp , count);

Where, p denotes the attribute word. The occurrence frequency of marked attribute word is reserved in the "FeatureCount.txt" in the form of < fp , count>, which is applied to derive the conditional probability of feature attribute.

(3) Classifier test

The result of training information is used in the test phase by simulating the known dataset, which is completed by two Hadoop Jobs. The probability of testing samples in certain sentimental category is calculated by the following pseudo code.

Input: CommentCount.txt/FeatureCount.txt/ Test samples

Output: <TestSample, result1 result2 result3>

Map:

#Read CommentCount.txt and FeatureCount.txt

Probability calculation that feature attribute belongs to each sentiment category

For each word in CommentCount.txt

Calculate probability

Context.write (fp , pos):

Combiner/Reducer:

Probability calculation that textual comment belongs to each sentiment category

For each comment in test file

Calculate the probability of each class

Context.write (TestSample, result1 result2 result3)

The results are storage in "Test_result.txt" file in the form < TestSample, result1 result2 result3>. The sentiment category with maximum probability is regarded and selected as the classification result, and it pseudo code is as follows.

Input: Test_result.txt

Output: <max_class, comment>

Map:

Select the maximum probability among the three alternatives

For each term in Test_result.txt

Compare result1 result2 and result3

Context.write (the biggest, comment)

Combiner/Reducer:

Context.write (max_class, comment)

3.3 Consumers behavior analysis using Saaty scale-based model

Previous publications mainly focus the polarity study of consumer's behavior, ignoring the multi-class rating of sentimental value. The consumer behavior preference is studied by mining the big data of textual comment online, along with introducing Analytical Hierarchy Process implementation steps proposed by Prof. Saaty in Pittsburgh University (He et al. 2017). The Saaty scale scoring technique is introduced to perform data mining on the collected textual comments, providing guidance on multiple classification in terms of sentimental value.

3.3.1 Saaty scale-based sentiment value calculation

On the basis of sentiment classification results of feature attributes, the quantitative influence of adverbs has been taken into consideration. The scoring method similar to Saaty's approach using weight coefficient is proposed to reflect the discrepant degree of different adverbs. Sentiment classification instances are presented in the Table 2.

Table 2. Classification instance of sentimental polarity

Instance	Comment sequence	Dictionary pairs of attribute feature	Emotional category	Adverb
Instance 1	1	<space, big>	Positive	Very
Instance 2	2	<appearance, look bad>	Negative	No adverb

To quantify the sentimental value of the textual comments, the adverbs, regarding as the weight co-efficient, are assigned to specific value on the basis of the emphasis degree. The sentimental value calculation steps of attribute class are presented as follows:

Step 1: The value of positive sentiment for attribute value is regarded as 1, and the negative sentiment value is assigned to -1.

Step 2: If there are adverbs, the weighted summation operation is performed to calculate the sentimental value based on weight coefficient illustrated in Table 3, and if there is no adverb, it will remain the original value.

Table 3 Weight co-efficient of different adverb

Adverb	too	very	extremely	quite	a little	Neutral
Weight coefficient	4	3	5	3	2	1

Step 3: The sentimental value of the attribute class is calculated based on Eq. (6), according to the scored value of each attribute word.

$$ACS = \text{SUM} (ATS) / N \quad (6)$$

Where ACS denotes the sentimental value of the attribute class, and ATS represents the scoring value of the attribute word. N is the total number of attribute words for every class.

3.3.2 Weight calculation of attribute feature

To discover preferences of vehicle consumers, the relative importance of attribute influencing the consumer behavior preference is derived by pair-wise comparison operations based on sentimental analysis (Awasthi et al. 2018). On basis of the Saaty

scoring rule presented in Table 4 (Jain et al. 2018), the multi-class sentiment value of each attribute is obtained. The construction rules are presented in Table 4.

Table 4 Construction of sentimental matrix using reverse emotion rule

Condition	Intensity of importance	Definition	Pair-wise comparison
$ ACS(A) - ACS(B) = 0$	Equal preferred	The two attribute classes (A and B) got the same score value	$x(A:B)=1$
$0 < ABS(ACS(A) - ACS(B)) \leq 1$	Somewhat more preferred	Both A and B are positive or negative, and $ ACS(A) > ACS(B) $	$x(A:B)=1:3$
$0 < ABS(ACS(A) - ACS(B)) \leq 1$	Somewhat more preferred	A and B have the different polarity, and $ ACS(A) > ACS(B) $	$x(A:B)=3$
$0 < ABS(ACS(A) - ACS(B)) \leq 2$	Strongly more preferred	Both A and B are positive or negative, and $ ACS(A) > ACS(B) $	$x(A:B)=1/5$
$0 < ABS(ACS(A) - ACS(B)) \leq 2$	Strongly more preferred	A and B have the different polarity, and $ ACS(A) > ACS(B) $	$x(A:B)=5$
$0 < ABS(ACS(A) - ACS(B)) \leq 3$	Very strongly preferred	Both A and B are positive or negative, and $ ACS(A) > ACS(B) $	$x(A:B)=1/7$
$0 < ABS(ACS(A) - ACS(B)) \leq 3$	Very strongly preferred	A and B have the different polarity, and $ ACS(A) > ACS(B) $	$x(A:B)=7$
$0 < ABS(ACS(A) - ACS(B)) \leq 4$	Extremely more preferred	Both A and B are positive or negative, and $ ACS(A) > ACS(B) $	$x(A:B)=9$
$0 < ABS(ACS(A) - ACS(B)) \leq 4$	Extremely more preferred	A and B have the different polarity, and $ ACS(A) > ACS(B) $	$x(A:B)=1/9$

Note: ACS (A) denotes the sentimental value of the attribute class, and $x(A:B)$, regarding as the element of sentiment matrix, is the relative preference value of the pair-wise attribute class comparison.

Different from traditional judgement matrix constructed by subjective Delphi technique, the establishment of judgement matrix is on the foundation of emotional analysis of textual comments. Regarding the sentimental matrix as the judgement matrix, the weight calculation steps of AHP method is employed (Awasthi et al. 2018; Zhou et al. 2016a). Based on the random consistency index, the the consistency test is conducted in Eq. (7)- (8).

$$CI = (\lambda_{max} - n) / (n - 1) \quad (7)$$

$$CR = CI / RI \quad (8)$$

3.4 The extended VIKOR-based for alternative ranking

The Saaty-based technique is employed to analyze consumer behavior preference through weight operations. To provide guidance for potential vehicle consumers, the VIKOR approach is modified to assist realize the intellectual product recommendation with respect to multiple criteria (Shemshadi et al. 2011; Zhou, Wang and Goh 2018). Through the VIKOR-based steps, we can derive the compromised solution with obtaining the ranking-list (Zhou, Wang and Lim et al. 2018). The best solution is generated based on the “closeness to the ideal” philosophy, started with-Metrix in Eq. (9).

$$L_{p,i} = \left\{ \sum_{j=1}^n \left[\frac{w_i(f_j^* - f_{ij})}{f_j^* - f_j^-} \right]^p \right\}^{1/p}, 1 \leq p \leq +\infty, i = 1, 2, \dots, m \quad (9)$$

On the basis of the consumer behavior analysis, the integrated Saaty scale-based VIKOR (SSC-VIKOR) approach is developed to analyze the purchasing preferences of vehicle consumes and conduct the performance evaluation for vehicle brand from big data perspective. The main stages of the proposed integrated method are as follows in Fig. 2.

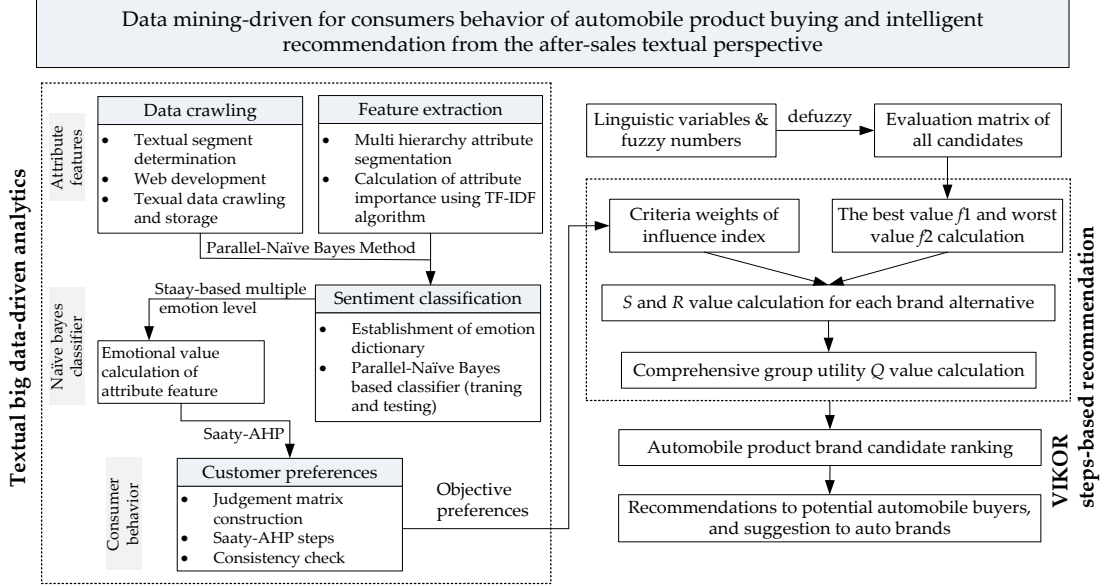


Figure. 2 The framework of the integrated methodology

From the proposed approach presented in Fig. 2, we can capture some insights on vehicle consumers' preference from online viewpoint, as well as the intellectual vehicle brand recommendation using textual comment data mining. Firstly, the parallel Naïve Bayes method is employed to perform sentiment classification on the basis of data crawling and hierarchical attribute analysis. Then, the Saaty-based scoring technique is applied to calculate the sentimental value of the attribute class. Finally, extended VIKOR-based steps are proposed, manifested in Fig. 2, by embedding the above-mentioned operations, where the VIKOR follows the previous publications (Zhou, Wang, Lin et al. 2016; Zhou, Wang and Samvedi 2018). After that, we can investigate consumers' preference from textual comments, and recommend the vehicle alternative ranking-list on the basis of S, R and Q value from big data perspective.

4 Results and discussion

To verify the proposed approach, a practical case analysis is presented in this section. Based on the consumer behavior preference analysis of online textual comments, the ranking-list of vehicle brand from big data viewpoint is derived and obtained, providing guidance for product purchasing.

4.1 Data collection and pre-processing



The 160 thousand forum comment items are regarded as experimental data which crawled from "Car home" (Chinese website of vehicle products). The extracted attribute class of description words calculated by TF-IDF algorithm is presented in Table 5.

Table 5 Attribute class and textual word details (for instance)

Attribute	Attribute word set
Car type	Haval H6, Chang'an CS35, Ruihu 7, Dihao GS, Rongwei RX5 etc.
Exterior	Shape, appearance, color, size, car body, front of the car etc.
Interior	Roof, floor, sit sets, steering wheel, storage box, seat cushion etc.
Space	Volume, space area, size etc.
Comfort	Comfortable, satisfied etc.
Power	Engine, throttle, tire size etc.
Fuel consumption	Oil consumption, fuel consumption per 100km etc.
Maneuverability	Chassis, steering, transmission, engine, parking-brake etc.
Cost-effective	Reference price, naked price, contracted price etc.
Stability	Stable, gentle, smooth driving etc.
Entertainment	3D Navigation, real-time road condition, auxiliary driving etc.
After-sale service	Repair & maintenance, consultation, insurance, 4S shop service etc.

Subsequently, the sentiment dictionary is constructed on the basis of the basic CNKI, NTUSD, and BosonNLP textbook, also consisting of the prevailing expressions in QQ and WeChat (social network in China). The mass crawled data from the "Wangci Website" (<http://wangci.net/word.html>) is regarded as online sentimental expressions, illustrated in Table 6.

Table 6 Description of constructed sentiment dictionary

Sentiment dictionary	Positive word	Instance	Negative word	Instance	Summary
Basic dictionary	7412	Pretty/comfortable etc.	12695	Crowded/ gas-guzzling etc.	20107
Emotional picture	17		33		50
Internet vocabulary	260	Top-level etc.	237	Heart-broken etc.	497

The performance indexes accuracy, recall rate and F1 value are employed to testify the validation of sentiment classification, and they are calculated by following Eq. (10) ~ (13) based on the mixed matrix. The construction of the mixed matrix is illustrated in Table 7 as follows.

Table 7 Establishment of the mixed matrix

Sentiment classification	Corrected classification	Wrong classification
Positive	TP (Positive items of corrected prediction)	FP (Positive items of wrong prediction)
Negative	TN (Negative items of corrected prediction)	FN (Negative items of wrong prediction)

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (10)$$

$$\text{Recall} = TP / (TP + TN) \quad (11)$$

$$\text{Precision} = TP / (TP + FP) \quad (12)$$

$$F1 = (2 * P * R) / (P + R) \quad (13)$$

4.2 Sentiment classification

Due to the discrepancy of the word dictionary when dealing with the unstructured information, there may exist different classification results for the same data samples. Therefore, eight experiments are set up in our research for comparison, shown in Table 8.

Table 8 Experiment scenarios of sentiment classification

Experiment item	Condition 1	Condition 2	Condition 3
Experiment 1	Without attribute weight	Basic dictionary	Traditional Naïve Bayes method
Experiment 2	Without attribute weight	Basic dictionary	Parallel Naïve Bayes classification
Experiment 3	Without attribute weight	Full dictionary	Traditional Naïve Bayes method
Experiment 4	Without attribute weight	Full dictionary	Parallel Naïve Bayes classification
Experiment 5	Considering attribute weight	Basic dictionary	Traditional Naïve Bayes method
Experiment 6	Considering attribute weight	Basic dictionary	Parallel Naïve Bayes classification
Experiment 7	Considering attribute weight	Full dictionary	Traditional Naïve Bayes method
Experiment 8	Considering attribute weight	Full dictionary	Parallel Naïve Bayes classification

Results of sentimental classification in different experimental scenarios are presented in the following Table 9, and the accuracy, recall rate and F1 value index is used to verify its performance.

Table 9 Comparison result of sentiment classification in experimental scenarios

Experiment item	Accuracy	Recall rate	F value	Operation time
Experiment 1	-	-	-	Not enough storage
Experiment 2	63.8%	45.7%	53.3%	328S
Experiment 3	-	-	-	Not enough storage
Experiment 4	66.8%	48.9%	56.5%	328S
Experiment 5	-	-	-	Not enough storage
Experiment 6	64.5%	47.1%	54.5%	328S
Experiment 7	-	-	-	Not enough storage
Experiment 8	67.5%	50.4%	57.7%	328S

From the experimental results in Table 9, we can notice the performance of the proposed Parallel Naïve Bayes classifier, as well as the effectiveness of the full dictionary and attribute word weight consideration in practical.

4.3 Consumer behavior preference analysis

According to the Saaty scoring method, the sentimental value of each attribute class is derived as Table 10 illustrated.

Table 10 Sentiment value of the attribute class

Attribute class	Car type	Exterior	Interior	Space	Comfort	Power
Sentiment value	3.2404	4.2521	4.1013	2.7381	0.5381	-2.4513
Attribute class	Fuel consumption	Maneuverability	Cost-effective	Stability	Entertainment	After-sale service
Sentiment value	-1.9513	-3.4620	-4.4352	1.0360	3.2013	0.6189

According to the judgement matrix, we got the eigenvalue $\lambda=13.691$. Through the consistency test that $CI=CR/RI=0.153/1.54=0.0998<0.1$, we can deduce the following preference results found in Table 11.

Table 11 Weight of consumers' behavior preference

Attribute class	Car type	Exterior	Interior	Space	Comfort	Power
Preference	1.8%	1.4%	1.6%	3.4%	8.9%	12.9%
Attribute class	Fuel consumption	Maneuverability	Cost-effective	Stability	Entertainment	After-sale service
Preference	9.2%	18.7%	25.1%	6.5%	2.9%	7.5%

Through the big data analytics from online textual comments, the most significant factor influencing customers' purchasing is the cost-effective value characteristic, which means Chinese consumers still prefer the cheap vehicle product with high quality performance. It caters to the strategic plans of domestic automobile industry (Zhou, Wang, Lin et al. 2016).

4.4 Recommendation by the ranking results

To provide guidance on vehicle product recommendation for potential consumers, the derived weights of analyzed attribute class are embedded into VIKOR steps, where the attributes are regarded as the multiple conflicting criteria. The advantage of the proposed intelligent recommendation is on the basis of big data analytics of textual comments, avoiding the subjective bias determined in the traditional MCDM approach. The specific information and detail scores with respect to each attribute class are evaluated in Table 12.

Table 12 Evaluation scores of the three vehicle candidates in "Car home" website

Criteria	Car type			Exterior			Interior			Space			Comfort			Power		
Score	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3
	5.00	5.00	4.98	4.87	4.69	4.72	4.57	4.89	4.62	3.87	4.13	4.08	4.16	3.97	4.09	4.07	4.87	4.63
Criteria	Fuel consumption			Maneuverability			Cost-effective			Stability			Entertainment			After-sale service		
Score	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3
	3.97	3.75	4.97	4.01	4.83	4.72	3.49	4.35	4.36	4.15	3.86	4.17	2.87	4.98	4.05	4.13	3.15	4.97

On the basis of the proposed SSC-VIKOR steps shown in Fig. 2, the ranking-list of vehicle candidates is presented in Table 13 ($v=0.5$).

Table 13 Ranking-list of the three vehicle candidates

Vehicle candidate	S value/ Ranking	R value/ Ranking	Q value/ Compromise Ranking
A1	0.69 (3)	0.25 (3)	1 (3)
A2	0.34 (2)	0.09 (2)	0.15 (2)
A3	0.24 (1)	0.08 (1)	0 (1)

According to the obtained results presented in Table 13, the two required conditions on the acceptance advantage and stability of the methodology are checked and verified:

The formula $Q(A^{(2)}) - Q(A^{(1)}) = Q(A2) - Q(A3) = 0.15 > 0.08$ is tested, and the top priority of vehicle candidate is always candidate A3, which means the two conditions are both satisfied. The results show that A3 is the best vehicle candidate from textual comment perspective, verifying the proposed method could provide a recommendation for potential consumers.

4.5 Discussion

Results from mass textual comments of vehicle product illustrate that "cost-effectiveness" characteristic is the most important factor that vehicle consumers care. It is the satisfaction recognition of vehicle consumers that drives the industrial development. Those vehicle types with high cost-effective performance are showing prevailingly welcomed for potential consumers in Chinese market, which motivates industrial factories to perform the continuous quality improvement practice concerning

economy of quality. It is myopia for vehicle organizations to excessively concentrate on the manufacturing cost in production phase. To achieve the high “cost-effectiveness”, industrial brands should focus on the economy of quality from the total lifecycle viewpoint, instead of the local stage (Zhou, Wang and Goh et al., 2019). That caters to the competitive strategy transformation (from “low cost” strategy advantage to the strategic “low cost with high quality” prospect) recently implemented by the Chinese domestic auto-factories (Zhou, Wang and Samvedi 2018). Then, maneuverability, power and fuel consumption criteria are also much focused by vehicle consumers, manifesting that car users prefer to products with higher performance and better experience.

The extended SSC-VIKOR model realizes the intellectual recommendation for potential vehicle users from mass textual perspective. The recommendation result is based on the following alternative ranking list $A3 > A2 > A1$ in the practical case, and A3 is the best alternative with a high robustness in terms of parameter v , showing the most popular one. Besides, the preference analysis and criteria weight are derived by the sentimental judgement matrix, instead of the subjective judgements of expert panels. The big data analytic on mass textual comments contributes to the subjectivity reduction in experts-oriented decision-making methods in previous publications. That is crucial differences with previous MCDM techniques, such as AHP, Delphi, ANP and expert-based recommendation. The Saaty scale-based scoring rule is developed to derive the criteria weight based on the sentimental value. Preference of vehicle consumers & ranking results of vehicle brand from consumers’ perspective are obtained through the formulated framework in our research, which provides meaningful insights for both industrial auto-factories and potential vehicle consumers.

5 Theoretical and managerial implications

This research serves both scientific and practical contributions to domestic vehicle industry management by providing some theoretical and practical implications on vehicle consumer analysis and vehicle product recommendation. In this section, we address the theoretical implications to vehicle industry management and provide managerial implications for industrial application.

5.1 Implications to theoretical knowledge

This study contributes to theoretical knowledge on automobile product management by developing a big data analytic-based SSC-VIKOR approach, thereby probe into better understand what attracts vehicle consumers’ buying, and more objective procurement recommendations for potential vehicle buyers in an intelligent way. The contribution to existing research is twofold. Firstly, we attempt to reveal the vehicle consumers’ behavior from a novel angle. The online textual comments from end-users, regarding as the data sources of this research, provides insightful information on vehicle marketing and product improvement. Secondly, an integrated SSC-VIKOR approach is proposed to assist on consumers’ behavior analysis and product recommendation from the big data point of view.

This research develops a big data analytic-based approach to achieve the data mining, excavating the un-structured data coming from textual comments of the vehicle website. The textual big data-driven analytics is performed to derive the preferences of vehicle consumers, including data crawling, feature extraction,

sentiment classification and consumer behavior analysis, whose procedures are embedded into VIKOR steps, assisting to achieve the vehicle recommendation for potential buyers.

5.2 Implications to industrial practice and managerial insights

From a managerial point of view, the big data analytic-based method in our research enables automobile manufacturers and retailers to better understand and discover the consumption preferences of their consumers, facilitating to launch strategic marketing strategies and quality improvements. Specifically speaking, the data information coming from textual comments provides the most intuitive evidence on automobile product utilization. The results analyzed by data mining techniques help retailers to discover and investigate the preferences of vehicle consumption, contributing to the marketing strategy establishment in a more precise way. Besides, the intelligent recommendation by the proposed SSC-VIKOR method assists potential consumers to make determinations on vehicle purchasing from an objective viewpoint.

Meanwhile, the unwelcome items derived can provide warning on accurate improvement. Different with previous quality improvement practices (Zhou, Wang and Samvedi 2018), this evidences of product feedback are unstructured information comes from the perspective of end-users, instead of the structured statistical information. The textual comments generated by vehicle consumers can provide the most direct and effective evidence on product utilization and taking full advantage of this kind of consumption information will contribute to product promotion.

6 Conclusions

Understanding consumers' preferences enables to provide guidance for automobile manufactures and product managers to develop a more precise vehicle for customers. Also the objective recommendation assists potential consumers make decisions on vehicle purchasing.

As we all know, the consumers' experience and cognition are the inexhaustible power for auto factory to perform continuous improvement, and knowing what attracts vehicle consumers is of great significance to the performance enhancement and brand reputation (Zhou, Wang and Samvedi 2018). This research is motivated by the increasing tendency of vehicle consumption and the mass online comments. The data analysis on online textual comments probes a novel insight for the precise management of auto factories, instead of the traditional questionnaire survey and empirical study. A novel Saaty scale-based VIKOR (SSC-VIKOR) approach is designed to analyze the online textual comments using big data analytics.

This study serves both scientific and practical contributes on the development of Chinese domestic automobile industry. Firstly, the construction of hierarchical attribute set assists to identify the essential attribute, and the attribute word weight using TF-IDF algorithm is taken into account for consumers' behavior preference analysis. Then, the full dictionary is developed on the basis of the fundamental sentimental dictionary and prevailing expressions in website. To improve the efficiency of sentimental classification, the parallel Naïve Bayes classifier is proposed, following the sentimental value calculation of the attribute class. Thirdly, on the basis of the Saaty-based scoring principle, the reverse emotional rules are regulated to formulate the sentiment matrix, realizing the

multi-level sentimental classification. The construction of the judgment matrix using big data analytics in this process enables to reduce the subjectivity of AHP, revealing the consumers' preference from mass textual comments instead of the experts' judgments. Finally, the weight of preference index is embedded into VIKOR steps, assisting potential vehicle consumers to make procurement decision-making by the alternative ranking-list recommendation.

However, this research also has some limitations. Firstly, the analysis results are derived based on the crawling comment items from "Car home" website, not containing other vehicle forums. Secondly, there is a general analysis on the vehicle consumer consumption behavior, ignoring the more detail analysis on different segments in different dimensions (nation, area, age, gender, and occupation etc.). Thirdly, the attribute class category is based on the established evaluation framework of vehicle product on "Car home" website, and more specific criteria can be developed in the future study. The much more in-depth analysis for different crowd groups will definitely contribute to the more precise marketing and quality improvement.

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